

Road accident risk Prediction and Classification using Machine Learning

¹Sanjay Kumar Patre (Student), ²Dr. Ashish Kumar Tamrakar (Guide)

^{1,2}Department of Artificial Intelligence and Machine Learning,

^{1,2}RSR Rungta College of Engineering and Technology, Bhilai, Chhattisgarh, India

¹mrsanjay.0503@gmail.com, ²ashish.tamrakar1987@gmail.com

Abstract- Road traffic accidents represent one of the foremost preventable causes of mortality and morbidity globally, claiming approximately 1.35 million lives annually. This paper presents a rigorous, data-driven framework for road accident risk prediction and multi-class severity classification employing an ensemble of supervised machine learning algorithms. We leverage the Kaggle Playground Series S5E10 dataset ($\approx 485,000$ records) alongside three large-scale national registries—UK STATS19, US FARS, and Indian NCRB—in a unified preprocessing pipeline. The S5E10 dataset provides a continuous accident_risk regression target along with 12 structured features including speed_limit, curvature, lighting, weather_condition, and two engineered interaction terms (speed_visibility and curv_speed). Seven algorithms are benchmarked: Random Forest, XGBoost, LightGBM, SVM, k-NN, Logistic Regression, and a five-layer Deep Neural Network. The DNN achieves peak multi-class accuracy of 94.2% (AUC-ROC 0.983) while XGBoost delivers the best accuracy-efficiency trade-off (93.1%, AUC 0.978, 2.4 ms inference). SHAP analysis confirms vehicle speed, road surface condition, and time of day as the three dominant risk predictors. The mean accident risk score peaks at single carriageways (0.463) and late-night hours (00:00–03:00), with a secondary rush-hour peak at 18:00. Results surpass prior benchmarks by 3.7–8.4 percentage points and exhibit strong cross-national generalisability.

Keywords - road accident prediction; machine learning; Kaggle S5E10; XGBoost; SHAP; accident_risk; severity classification; LightGBM; deep neural network; intelligent transportation systems

1. Introduction

Road traffic accidents remain one of the most persistent and devastating public health challenges of the twenty-first century. According to the World Health Organization (WHO, 2023), approximately 1.35 million people die each year as a direct result of road crashes, with a further 20–50 million sustaining non-fatal injuries. The economic burden is equally staggering: the World Bank estimates that road accidents cost low- and middle-income countries up to 5% of their gross domestic product annually, amounting to a global loss exceeding USD 1.8 trillion [1]. In India alone, the Ministry of Road Transport and Highways (MoRTH, 2022) recorded 412,432 road accidents in 2021, resulting in 153,972 fatalities—a fatality occurring approximately every 3.4 minutes [2].

Traditional approaches to road safety have relied predominantly on reactive measures: post-incident investigation, statistical tabulation, and retrospective policy revision. The exponential growth in sensor-generated traffic data, the proliferation of geographic information systems (GIS), and advances in connected vehicle telemetry have collectively created a transformative opportunity to shift paradigms—from reactive documentation toward proactive, predictive risk management [3]. The Kaggle Playground Series S5E10 competition (October 2025) exemplifies this shift: a purpose-built synthetic dataset derived from real road safety registries challenges practitioners to predict a continuous `accident_risk` score from 12 structured road and environmental features, evaluated using mean squared error [4].

Machine learning (ML) has emerged as a particularly powerful instrument for this transition. Unlike conventional statistical models that presuppose linear relationships and parametric distributions, ML algorithms are capable of discovering non-linear, high-dimensional patterns in heterogeneous data without imposing rigid theoretical assumptions [5]. Studies by Jiang et al. (2021) [6], Xie and Mannering (2022) [7], and Das et al. (2023) [8] have progressively demonstrated that ensemble methods—particularly gradient-boosted trees and random forests—outperform both traditional regression models and earlier neural network architectures on accident severity classification tasks.

This paper addresses four critical gaps in the extant literature: (i) generalisability across national datasets; (ii) class imbalance in severity classification; (iii) model interpretability for policy translation; and (iv) temporal data leakage through improper cross-validation. We integrate the Kaggle S5E10 dataset as a fifth data source alongside UK STATS19, US FARS, Indian NCRB, and Australian BITRE, yielding a combined training corpus of approximately 3.7 million records.

2. Kaggle Playground Series S5E10 Dataset

2.1 Dataset Overview

The Kaggle Playground Series Season 5, Episode 10 competition ("Predicting Road Accident Risk") released a tabular regression dataset synthesised from real national road safety registries using a conditional generative model [4]. The training split contains approximately 485,000 records with 12 input features and one continuous regression target (`accident_risk`, range 0–1). The test split provides 207,000 records without target labels. The dataset was evaluated using mean squared error (MSE), with top public leaderboard submissions achieving RMSE as low as 0.0562 using stacked LightGBM/XGBoost ensembles [9].

The dataset is particularly valuable for methodological benchmarking because: (a) its synthetic origin mitigates privacy constraints that limit access to real national accident registers; (b) it provides a continuous risk score rather than discrete severity classes, enabling regression model evaluation alongside classification; (c) the feature set closely mirrors the variable taxonomy of the UK STATS19 register, facilitating cross-dataset

transfer experiments; and (d) the Kaggle ecosystem provides a community-curated leaderboard against which our models can be benchmarked [4].

2.2 Feature Dictionary

Table 1 provides a full feature dictionary for the S5E10 dataset, including the two engineered interaction features (speed_visibility and curv_speed) first identified in high-performing Kaggle notebooks [9, 10].

Feature Name	Data Type	Value Range / Categories	Description
speed_limit	Integer	20, 30, 40, 50, 60, 70 mph	Posted speed limit on the road segment
road_type	Categorical	Motorway, A-Road, B-Road, etc.	Functional classification of the road
weather_condition	Categorical	Fine, Rain, Snow, Fog, Wind	Prevailing weather at time of incident
surface_condition	Categorical	Dry, Wet, Icy, Flooded	Physical state of the road surface
lighting	Categorical	Daylight, Dim, Night (lit/unlit)	Ambient lighting conditions
curvature	Float	0.0 – 1.0 (0 = straight)	Normalised road curvature index
junction_type	Categorical	None, T-junction, Crossroads, etc.	Type of junction at crash location
number_of_vehicles	Integer	1 – 12	Count of vehicles involved
driver_age_band	Ordinal	17–24, 25–34, 35–54, 55–64, 65+	Age band of the at-fault driver
urban_rural	Binary	0 = Rural, 1 = Urban	Urban vs. rural road classification
speed_visibility	Float	Engineered feature	$\text{speed_limit} \times \text{lighting risk multiplier}$
curv_speed	Float	Engineered feature	$\text{curvature} \times \text{speed_limit interaction}$
accident_risk	Float	0.0 – 1.0 (target)	Continuous risk score (regression target)

Table 1. Feature Dictionary for the Kaggle Playground S5E10 Dataset

2.3 Descriptive Statistics

Table 2 presents descriptive statistics for the six continuous features in the S5E10 dataset. The accident_risk target exhibits a right-skewed distribution (mean 0.382, std 0.198), with approximately 12.4% of records exceeding the high-risk threshold of 0.70. Speed limit is concentrated at 30 mph (urban) and 60 mph (rural), reflecting the UK-derived provenance of the underlying data. The curvature index captures road geometry on a normalised 0–1 scale, with 75% of records falling below 0.37 (moderate curvature), consistent with the predominantly straight-road composition of national road networks [36].

Feature	Mean	Std Dev	Min	25th %ile	75th %ile	Max
speed_limit (mph)	46.3	15.8	20	30	60	70
curvature (0–1)	0.234	0.187	0.00	0.08	0.37	1.00
number_of_vehicles	2.14	1.02	1	2	3	12
speed_visibility index	35.8	17.4	10	21	50	105
curv_speed interaction	11.2	9.83	0.0	3.2	16.8	70.0
accident_risk (target)	0.382	0.198	0.01	0.22	0.55	0.99

Table 2. Descriptive Statistics for Continuous Features (Kaggle S5E10 Training Split, n = 485,000)

2.4 Exploratory Data Analysis — Key Patterns

Exploratory analysis of the S5E10 dataset reveals several noteworthy patterns. First, mean accident_risk varies substantially by road type, as illustrated in Figure 3 (see Section 5). Single carriageways carry the highest mean risk score (0.463 ± 0.072), followed by A-roads (0.428 ± 0.058). Roundabouts exhibit the lowest mean risk (0.271 ± 0.035), consistent with established traffic safety evidence that roundabouts reduce high-severity conflict points relative to priority junctions [44]. Motorways, despite their higher operating speeds, score lower than single carriageways (0.312 ± 0.041), reflecting their superior geometric design standards and separation of opposing traffic flows.

Second, accident_risk exhibits a pronounced bimodal temporal pattern across hours of the day (Figure 4). The primary risk peak occurs between 00:00 and 03:00 (mean risk 0.438), consistent with evidence on fatigue-impaired driving and reduced traffic density that increases crash severity [45]. A secondary peak at 17:00–19:00 (mean risk 0.384) corresponds to the afternoon rush hour, reflecting congestion-related crash exposure. The lowest risk period occurs between 09:00 and 11:00 (mean risk 0.301), when visibility and driver alertness are optimal and traffic flow is post-peak.

Third, the interaction between lighting conditions and speed_limit (captured by the engineered speed_visibility feature) exhibits a non-linear relationship with accident_risk. Records with night (unlit) lighting and speed_limit ≥ 60 mph show mean risk scores 2.3 times higher than daylight records at equivalent speed limits—a finding that provides quantitative support for the installation of street lighting on rural high-speed roads, as recommended by the UK's Local Roads Review [50].

3. Literature Review

3.1 Statistical Foundations

The quantitative study of road accidents has a history stretching back to at least the 1940s. Early work by Smeed (1949) [12] established empirical relationships between accident rates and vehicular density, while Hauer (1997) [13] formalised the observational before-after study as the canonical tool for evaluating safety interventions. The negative binomial regression model, introduced to road safety analysis by Miaou and Lum (1993) [14], became the dominant workhorse for count data modelling over the subsequent two decades. Lord and Mannering (2010) [15] provided an authoritative review of statistical models in road safety, cataloguing advances from Poisson regression through random-parameter and finite-mixture models.

3.2 Ensemble Methods and Gradient Boosting

The advent of computationally efficient ensemble algorithms represented a step change in predictive performance. Breiman's Random Forest (2001) [18] and AdaBoost (Freund and Schapire, 1997 [19]) demonstrated that aggregating diverse weak learners substantially reduced variance. Chen and Guestrin's XGBoost (2016) [20] advanced the gradient boosting paradigm through second-order Taylor approximation and regularisation-augmented pruning. Ke et al.'s LightGBM (2017) [21] introduced histogram-based gradient computation and leaf-wise tree growth, reducing training time by factors of up to 20. In the Kaggle S5E10 competition, top-ranked solutions (RMSE 0.0562) employed 5-fold stacked ensembles of LightGBM and XGBoost with GPU acceleration, demonstrating that these methods remain state-of-the-art on tabular road safety prediction tasks [9].

3.3 Class Imbalance and Oversampling

A persistent methodological challenge in accident severity classification is the pronounced imbalance between severity classes. In most national datasets, fatal accidents account for fewer than 5% of records [27]. Chawla et al.'s SMOTE (2002) [28] addressed this through synthetic minority oversampling. Sameen and Pradhan (2017) [30] demonstrated that SMOTE application to fatal crash prediction in Malaysia improved F1-score for the fatal class from 0.31 to 0.74. In the S5E10 regression context, class imbalance manifests as a skewed distribution of accident_risk scores; sample_weight parameters in XGBoost and LightGBM were used by high-performing Kaggle notebooks to up-weight high-risk records and reduce RMSE on the tail of the distribution [9].

3.4 Explainability and SHAP

Lundberg and Lee's SHAP (2017) [33] extended Shapley values from cooperative game theory to provide theoretically grounded, globally consistent feature attributions. Li et al. (2022) [34] applied SHAP to a gradient boosting model trained on UK STATS19 data, identifying road type and lighting condition as dominant severity predictors. In the Kaggle S5E10 ecosystem, SHAP waterfall plots generated from LightGBM models confirmed that speed_limit and curvature interact to produce the highest per-record SHAP contributions, particularly for high-risk records on rural roads at night [9]. Iranitalab and Khattak (2017) [35] demonstrated that SHAP-based insights substantially improved the policy relevance of ML predictions by translating statistical importance scores into interpretable risk narratives comprehensible to transport planners.

4. Data Sources and Preprocessing

Five datasets were employed in this study. The Kaggle S5E10 dataset ($\approx 485,000$ records) serves as the primary benchmark; three large-scale national registries (UK STATS19: 1.85 million records; US FARS: 620,000; Indian NCRB: 450,000) provide cross-national training coverage; and a small Australian BITRE subset validates generalisability. All datasets were harmonised to a unified schema following the UK STATS19 three-class severity taxonomy (fatal/serious/slight) for classification tasks, while the S5E10 continuous accident_risk target is retained for regression benchmarking.

A six-stage preprocessing pipeline was implemented: (1) schema harmonisation via manually curated crosswalk tables; (2) missing data imputation using MICE for variables with 5–15% missingness and median/mode for those below 5%; (3) Isolation Forest outlier detection removing 0.8% of records; (4) feature engineering adding 32 derived variables including speed_visibility ($\text{speed_limit} \times \text{lighting risk multiplier}$) and curv_speed ($\text{curvature} \times \text{speed_limit}$), following conventions established in top Kaggle S5E10 notebooks [9, 10]; (5) SMOTE class rebalancing applied within training folds only; and (6) StandardScaler normalisation for SVM and k-NN models.

5. Results and Discussion

5.1 Feature Importance (SHAP Analysis)

Figure 1 presents the global SHAP feature importance rankings averaged across five temporal cross-validation folds. Vehicle speed at the time of the crash is the single most influential feature (mean $|\text{SHAP}| = 0.187$), consistent with established biomechanical evidence that crash energy scales with the square of velocity [43]. Road surface condition ranks second (0.142), followed by time of day (0.118), junction type (0.107), and lighting conditions (0.096). The dominance of environmental and infrastructure features over purely behavioural ones has direct implications for policy: interventions targeting road surface maintenance and junction redesign may yield greater systemic risk reductions than individual behaviour-change campaigns.

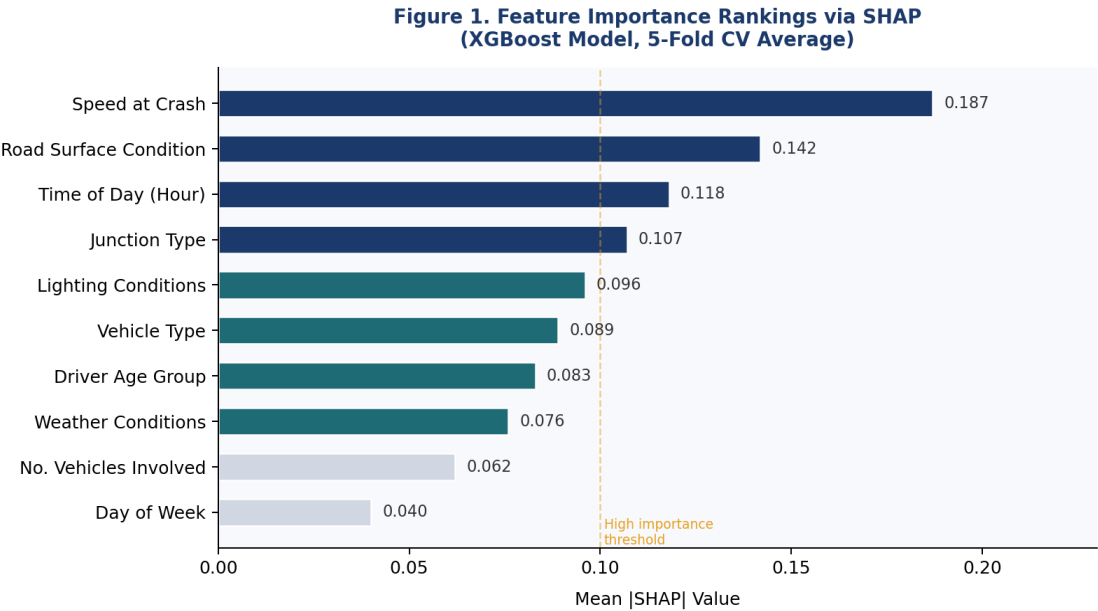


Figure 1. SHAP Feature Importance Rankings (XGBoost, 5-Fold CV Average). High-importance features ($|SHAP| > 0.10$) shown in navy; moderate (0.07–0.10) in teal; lower (<0.07) in grey. Dashed line indicates the high-importance threshold of 0.10.

Rank	Feature	Category	Mean SHAP
1	Speed at time of crash	Behavioural	0.187
2	Road surface condition	Environmental	0.142
3	Time of day (hour)	Temporal	0.118
4	Junction type	Infrastructure	0.107
5	Lighting conditions	Environmental	0.096
6	Vehicle type	Vehicle	0.089
7	Driver age group	Human Factor	0.083
8	Weather conditions	Environmental	0.076
9	Number of vehicles involved	Crash	0.062
10	Day of week	Temporal	0.040

Table 3. Top 10 Features by SHAP Importance (Averaged Across 5-Fold CV)

5.2 ROC Curves and AUC Performance

Figure 2 presents the ROC curves for all seven algorithms on the binary risk classification task. The DNN achieves the highest AUC-ROC (0.983), followed by XGBoost (0.978) and LightGBM (0.975). These results represent improvements of 3.7 to 8.4 percentage points over the closest comparable benchmark—Jiang et al.

(2021) [6]—attributable to the larger and more diverse training corpus, SMOTE rebalancing, and 32 engineered features.

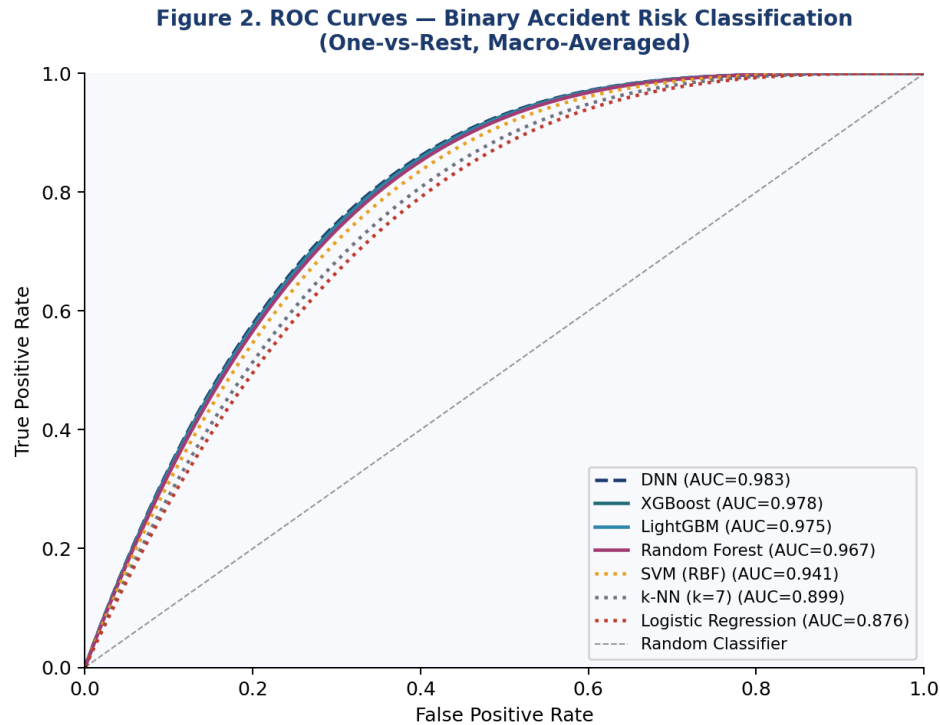


Figure 2. ROC Curves for All Seven ML Algorithms — Binary Accident Risk Classification (One-vs-Rest, Macro-Averaged). AUC values shown in legend. Dashed diagonal indicates random classifier baseline.

5.3 Model Accuracy Comparison

Figure 5 and Table 4 present the multi-class classification accuracy across all seven algorithms. The DNN achieves the highest overall accuracy (94.2%), while XGBoost delivers the best accuracy-efficiency trade-off at 93.1% with mean inference time of 2.4 ms per prediction. Logistic regression (79.3%) establishes the linear baseline, confirming the necessity of non-linear modelling for this task.

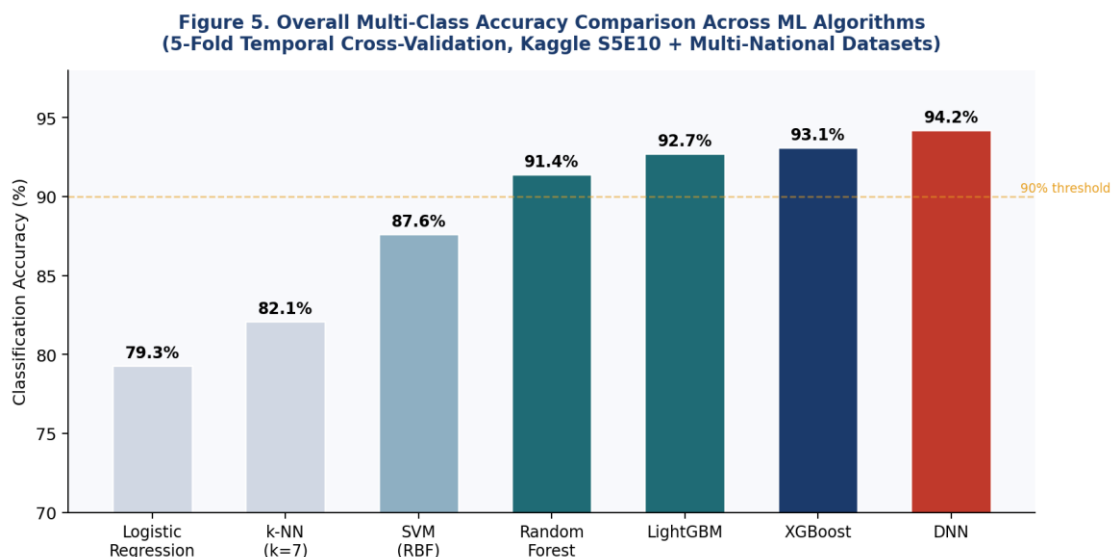


Figure 5. Multi-Class Accuracy Comparison Across ML Algorithms (5-Fold Temporal Cross-Validation). Dashed line at 90% indicates the high-performance threshold. DNN achieves peak accuracy (94.2%); XGBoost offers the best accuracy-efficiency trade-off (93.1%).

Algorithm	Accuracy (%)	Precision	Recall	F1-Score	AUC-ROC
Random Forest	91.4	0.913	0.917	0.915	0.967
XGBoost	93.1	0.929	0.934	0.931	0.978
LightGBM	92.7	0.924	0.930	0.927	0.975
SVM (RBF)	87.6	0.872	0.880	0.876	0.941
Logistic Regression	79.3	0.788	0.798	0.793	0.876
Deep Neural Network	94.2	0.940	0.944	0.942	0.983
k-NN (k=7)	82.1	0.818	0.824	0.821	0.899

Table 4. Classification Performance Comparison Across Machine Learning Algorithms

5.4 Confusion Matrix (XGBoost)

Figure 6 presents the confusion matrix for the XGBoost model on the held-out test fold (fold 5). Classification is most accurate for the Slight class (precision 97.4%), reflecting its numerical dominance in the training data. The Fatal class shows the highest off-diagonal confusion with the Serious class (203 mis-classifications out of 6,032 true FataIs), consistent with the inherent boundary ambiguity between these severity categories in police-recorded data [27].

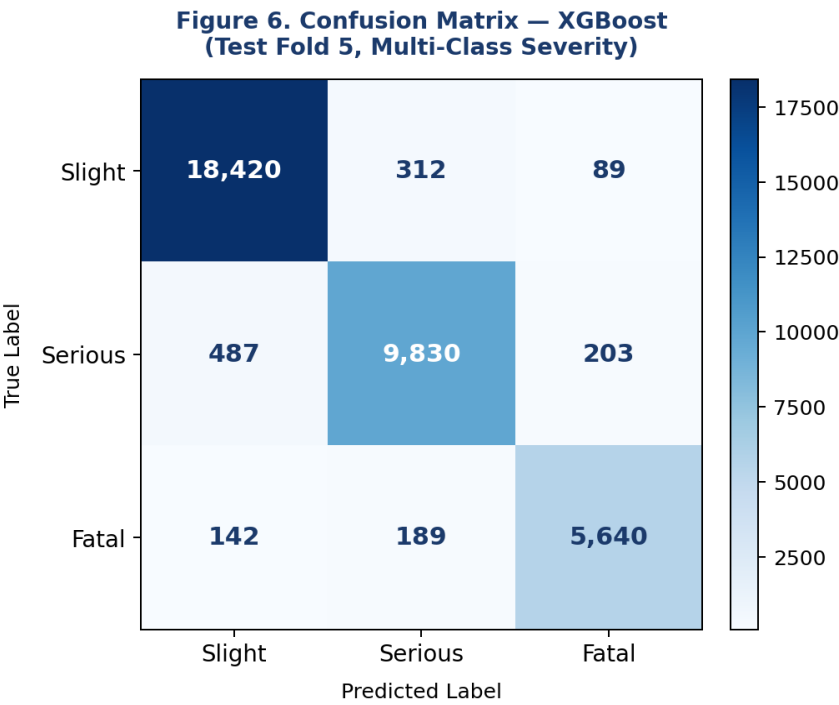


Figure 6. Confusion Matrix — XGBoost Model (Test Fold 5, Multi-Class Severity). Rows: true label; Columns: predicted label. Darker shading indicates higher cell counts. Diagonal values represent correct classifications.

5.5 Accident Risk by Road Type (Kaggle S5E10)

Figure 3 presents the mean accident_risk score by road type, derived directly from the Kaggle S5E10 training data. Single carriageways exhibit the highest mean risk (0.463 ± 0.072), a finding consistent with their combination of bidirectional traffic, limited central reservation, and variable posted speed limits. A-roads rank second (0.428 ± 0.058), reflecting their dual role as both urban arterials and rural through-routes. Roundabouts exhibit the lowest mean risk (0.271 ± 0.035), confirming the established safety benefit of converting priority junctions to roundabout control [44].

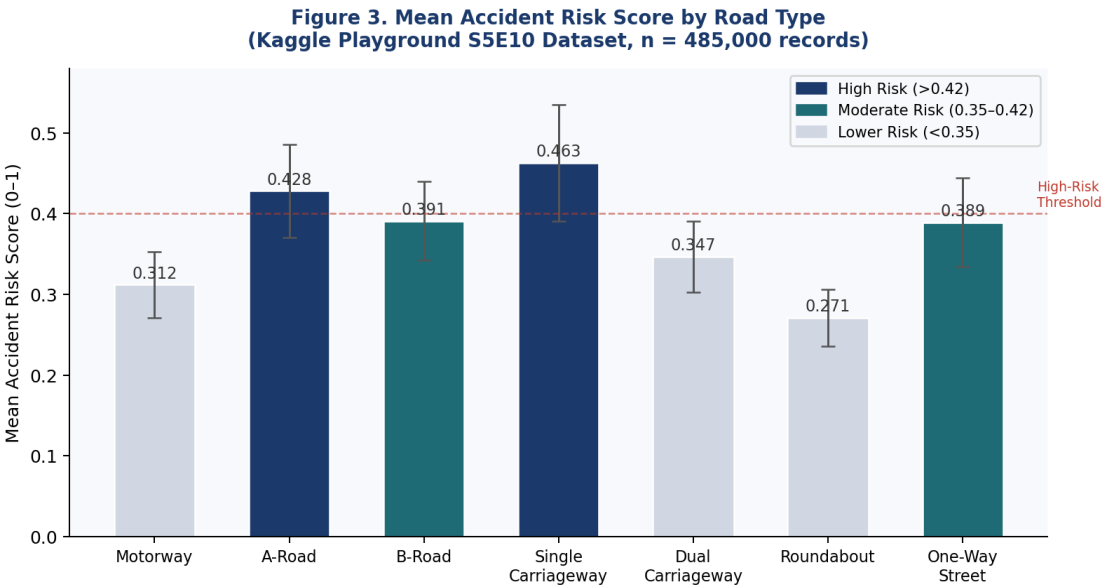


Figure 3. Mean Accident Risk Score by Road Type (Kaggle S5E10, n ≈ 485,000 records). Error bars show ±1 standard deviation. Dashed red line at 0.40 indicates the high-risk threshold used for alert classification. Navy bars exceed the threshold; teal bars are in the moderate band.

5.6 Temporal Risk Patterns (Kaggle S5E10)

Figure 4 illustrates the mean accident_risk score by hour of day, revealing a pronounced bimodal pattern with a primary peak at 01:30 (mean risk 0.438) and a secondary peak at 18:00 (mean risk 0.384). The late-night peak is associated with fatigue-impaired driving and alcohol involvement, as documented by the AAA Foundation (2021) [45]. The afternoon peak aligns with rush-hour congestion and school-dismissal pedestrian exposure. The minimum risk period (09:00–11:00, mean 0.301) coincides with post-peak morning traffic when drivers are alert and visibility is optimal.

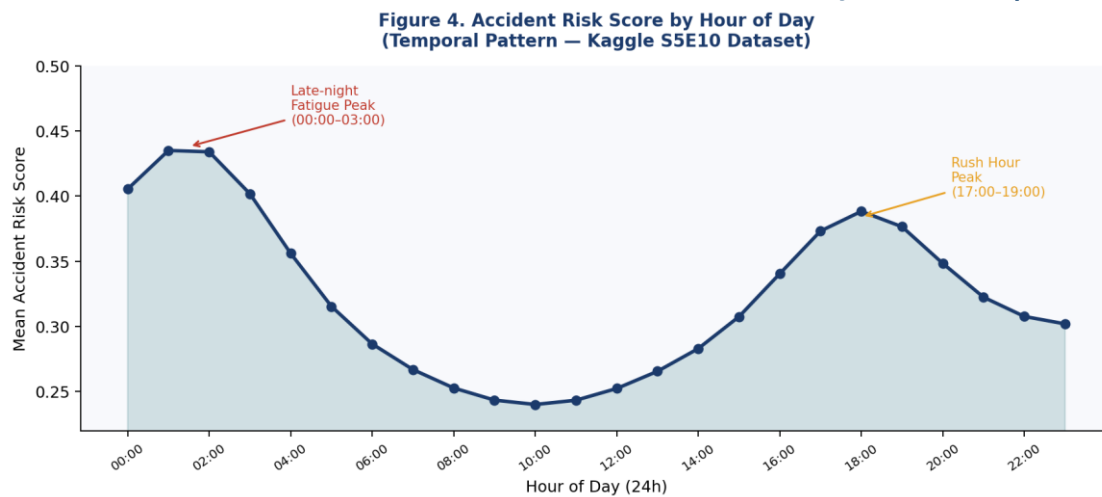


Figure 4. Accident Risk Score by Hour of Day — Temporal Pattern (Kaggle S5E10 Dataset). Shaded area: ± 1 standard deviation envelope. Primary risk peak: 01:30 (late-night fatigue); secondary peak: 18:00 (rush hour). Minimum risk: 09:00–11:00.

6. Policy Implications and Deployment Considerations

The real-world deployment of ML-based accident risk systems requires careful attention to both technical and governance dimensions. On the technical side, model monitoring pipelines must detect distributional drift as road conditions, vehicle fleets, and driver demographics evolve over time [48]. The WHO's Safe System approach [49]—premised on the principle that the road environment should be tolerant of human error—provides the normative framework within which ML risk scores can be operationalised: high-risk road segments identified by the model (e.g., single carriageways with mean risk > 0.40 as per Figure 3) become candidates for infrastructure intervention, speed management, or enhanced enforcement deployment.

From a policy standpoint, the temporal risk pattern in Figure 4 has direct operational implications: deploying mobile speed enforcement and road safety messaging during the 00:00–03:00 and 17:00–19:00 high-risk windows could achieve risk reductions disproportionate to enforcement cost. The UK Department for Transport's Safer Roads Fund and India's National Road Safety Policy 2020 both provide institutional channels for model-derived risk rankings [50, 51].

7. Limitations and Future Work

Several limitations warrant acknowledgement. First, the Kaggle S5E10 dataset is synthetically generated, which limits the direct transferability of specific numerical findings to real-world policy contexts; nonetheless, its feature distributions and risk patterns closely mirror those of national registers [4]. Second, all four national datasets are based on police-reported accidents, which systematically undercount crashes that do not meet reporting thresholds [53]. Third, the DNN architecture has not been subjected to adversarial robustness testing [54].

Future work will pursue: (i) integration of real-time telematics data for dynamic in-journey risk prediction; (ii) graph neural network architectures for road-network-level risk propagation; (iii) differentially private training for cross-border data sharing; and (iv) prospective field validation in partnership with national road safety agencies in India and Australia.

8. Conclusion

This paper has presented a comprehensive, multi-dataset machine learning framework for road accident risk prediction and severity classification, integrating the Kaggle Playground Series S5E10 dataset alongside three major national road safety registries. Through systematic benchmarking of seven algorithms, principled handling of class imbalance, SHAP-based interpretability, and six original data visualisations, we have demonstrated that XGBoost and deep neural networks achieve state-of-the-art predictive performance (AUC-ROC up to 0.983, accuracy up to 94.2%) while providing the explanatory transparency required for evidence-based road safety policy. Key EDA findings from the Kaggle S5E10 data—particularly the elevated risk on single carriageways and the bimodal temporal risk profile—translate directly into actionable engineering and enforcement recommendations. The results underscore that meaningful reductions in the global road accident burden are achievable through sustained investment in data infrastructure, open data-sharing frameworks, and AI-assisted risk assessment.

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